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A stepwise approach for identifying climate change induced socio-economic tipping points

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ABSTRACT

Climate change may cause socio-economic tipping points (SETPs), where the state of a socio-economic system abruptly changes to a fundamentally different state. While their potential existence is recognized, a systematic method for policy-relevant research on SETPs is lacking. This study introduces a stepwise approach for identification of SETPs that supports decision making under uncertain climate and socio-economic conditions. The approach is demonstrated with a stylized case study on the collapse of house prices (a SETP) in a coastal city, due to increasing flood risk from sea level rise. We explore four dynamic adaptive management strategies under a wide range of possible futures. We find that under scenarios with very high and rapid sea level rise, tipping points in real estate prices occur if the market responds to sudden changes in perceived flood risk rather than gradually adjusting prices to changes in flood risk in a rational manner. Such SETPs can only be avoided with a proactive strategy and when flood protection measures are implemented rapidly. Our approach can guide future studies on SETPs and seeks to move the study of SETPs towards a concept that provides perspective of action for policy makers.

1. Introduction

Climate change can have large impact on society and economy (IPCC, 2014). Gradual climate change can cause societal disruptions and large economic damage (Carleton and Hsiang, 2016; Nordhaus, 2018). In addition, climate tipping points (Box 1) can have dire socio-economic consequences (Lemoine and Traeger, 2016; Lontzek et al., 2015; Dietz et al., 2021). Much less attention has been paid to cases where the climate changes gradually, but the socio-economic system responds in a non-linear and abrupt fashion (Biggs et al., 2018; Kopp et al., 2016). Such climate change induced socio-economic tipping points (SETPs) are points where the state of a socio-economic system abruptly changes to a fundamentally different state, following relatively marginal climate change (van Ginkel et al., 2020). It is important for adaptation and mitigation policy development to understand if and how SETPs may occur.

Following Van Ginkel et al. (2020), this study defines a socio-economic tipping point (SETP) as a point of abrupt change of a socio-economic system into a new, fundamentally different state, using three criteria, see box 1. Two SETP subtypes are *impact* and *transformative response* tipping points (Maier et al., 2021; Winkelmann et al., 2022; van Ginkel et al., 2020), see box 1. An example of an

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impact-SETP is that at some degree of sea level rise, a low-altitude atoll island may suddenly become uninhabitable due to diminishing fresh water resources, increasing infrastructure damage during storm surge events, unaffordability of flood protection infrastructure and eventually permanent inundation (Magnan and Duvat, 2020; Storlazzi et al., 2018; Barnard et al., 2021). A *transformative response* SETP would be the proactive retreat from the islands before these impacts happen (Bordner et al., 2020, Siders et al., 2019). It is important for spatial-economic planners and capital investors to know if and under what conditions SETPs may happen, and what can be done to anticipate their causes and effects. However, the occurrence of SETPs is very uncertain due to complex systems interactions, model uncertainty, and uncertainty on future climate, socio-economic developments and adaptation (Biggs et al., 2018; van der Bolt et al., 2018; Kopp et al., 2019; Marchau et al., 2019).

In the emerging literature on tipping points in coupled socio-ecological systems most tipping points occur in the biophysical rather than the socio-economic realm (Filatova et al., 2016; Milkoreit et al., 2018). The few model studies describing climate change induced tipping points in the socio-economic domain (e.g. de Koning and Filatova, 2020; Hossain et al., 2017; Kabir et al., 2018) typically investigate a small set of possible futures or ignore adaptive policy change, which are highly relevant on longer time-scales when climate and socio-economic scenarios increasingly diverge, and adaptation to these new conditions can be expected (Biggs et al., 2018). Moreover, a perspective of action for decision makers is often missing (Verburg et al., 2016). What is lacking is a systematic stepwise approach for identification of climate change-induced SETPs, which accounts for uncertainties, many possible futures, and adaptive policy change and which can be used to support climate adaptation and mitigation policy.

Building blocks for such an approach can be found in the *Decision Making under Deep Uncertainty (DMDU)* research field dedicated to decision support in conditions of uncertain and complex system interactions (Marchau et al., 2019). *Decision Scaling* (Brown et al., 2012) and *Robust Decision Making (*Groves and Lempert, 2007*)* use computational techniques like *Scenario Discovery* to identify clusters of outcomes of interest under many possible futures (Bryant and Lempert, 2010; Kwakkel, 2017). Outcomes of interest may be threshold values in the model outcomes, time series with distinct model behaviour (Steinmann et al., 2020), or as we will show in this paper: SETPs. Identification of SETPs does not only require analysing when an indicator exceeds threshold conditions, but also requires identifying an abrupt shift from one to another stable state (e.g. Andersen et al., 2009; Truong et al., 2020).

The objective of this paper is to present a stepwise approach that identifies under what conditions SETPs may occur and guides policy aimed at preventing adverse SETPs or supporting positive SETPs. This is done by bringing together DMDU and tipping point literature in a stepwise approach and illustrating it with a stylized case study on flood risk in a coastal city like Rotterdam. We develop a model with characteristics of both a system-dynamic and an agent-based model, that simulates flood risk and house prices under

Box 1
Conceptualisation of climate change induced socio-economic tipping points

In contrast to their biophysical counterparts, where the tipping element is a (sub)system of the climate (Lenton et al., 2008) or ecosystem (Scheffer and Carpenter, 2003), the tipping element here is a delineated socio-economic system, and climate change is a driver (Fig. 1). After Milkoreit et al. (2018) and Van Ginkel et al. (2020), we define a socio-economic tipping point (SETP) as a point of: rapid, abrupt change compared to typical rates of change in the system (Criterion 1); indicating a transition from one to another relatively stable state (Criterion 2); these states being fundamentally different (Criterion 3). Strict system-dynamic conceptualisations such as mathematical bifurcations satisfy these criteria, while they also leave room for a more qualitative conceptualisation where argumentation shows that these three criteria are satisfied.

Two types of SETPs (Van Ginkel et al., 2020; Maier et al., 2020) are impact and response tipping points (Fig. 1). Impact SETPs refer to cases where the state shift occurs due to autonomous, endogenous system dynamics and insufficient human action. Some examples are: slow-onset climate hazards tipping a region to a reinforcing system state where people seek to migrate out of the region (Kopp et al., 2016; Kabir et al., 2018; McLeman et al., 2017); increasing flood risk causing a collapse of an established natural hazard insurance system (Tesselaar et al., 2020); or a retreating snowline causing bankruptcy of low-altitude ski resorts (Vaghefi et al., 2021). These examples are predominantly ‘negative’, given their close connection to climate change impact and natural disaster impact literature, but in principle they can also be ‘positive’, e.g. when the new climate conditions open new opportunities for agriculture. One reason for SETPs may be that critical limits to human adaptation are reached (Thomas et al., 2021).

Response SETPs refer to cases where the socio-economic structure is deliberately transformed by human action, in anticipation to foreseen impacts. Rooted in innovation and change theory (e.g. Rogers, 1962), and popularized by Gladwell (2000), this literature is predominantly ‘positive’ and seeks to benefit from non-linear system change to achieve abrupt, fundamental societal change to meet adaptation and mitigation challenges (Burch et al., 2017, Tàbara et al., 2021). Transformative adaptation refers to adaptation actions that fundamentally change a socio-economic system (Fedele et al., 2019; Garschagen and Solecki, 2017; Kates et al., 2012; Berrang-Ford et al., 2021). Transformative mitigation, often referred to as ‘social tipping’, refers to rapid, contagious spreading of behaviours, opinions, knowledge, technology, and social norms causing a shift to a socio-economic system with strongly reduced carbon emissions (Otto et al., 2020; Stadelmann-Steffen et al., 2021; Winkelmann et al., 2022).

Regardless of its negative connotation in climate change impact literature, we explicitly intend to include positive system shifts as well (Otto et al., 2020; Tàbara et al, 2018). In fact, the desirability of socio-economic system change is case-specific and subjective: the same tipping point might be opportune for some stakeholders that benefit from the new state, but at the same time be destructive for others that depend on the old state (Young, 2012).

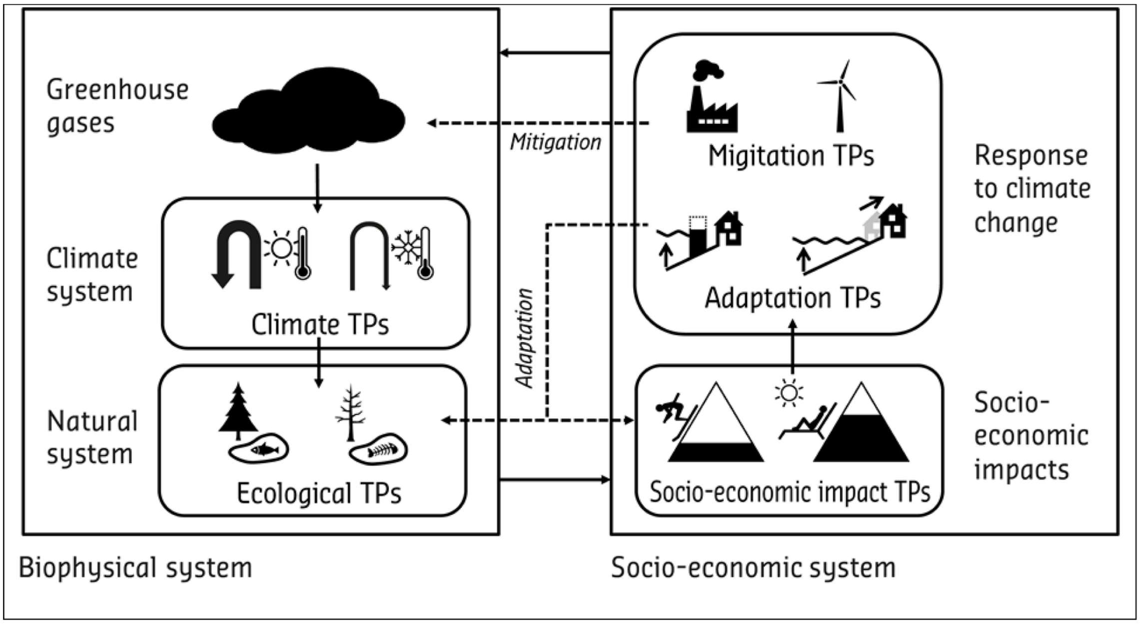

Fig. 1. Types of tipping points positioned in the archetypical cause-effect chain from greenhouse gas emissions to the climate and other natural systems, to socio-economic system impacts and human response. Source: Van Ginkel et al., 2020, CC BY License.

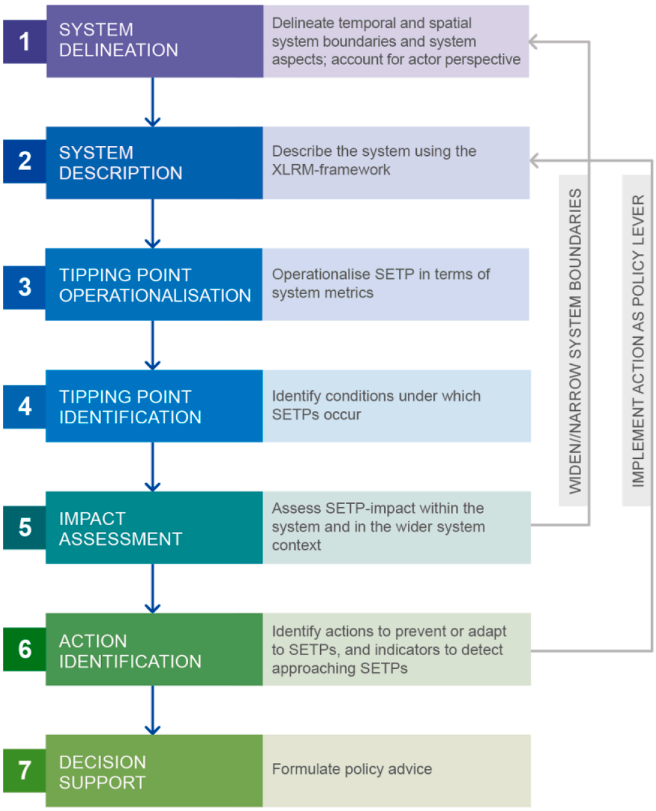

Fig. 2. Overview of the stepwise approach. The XLRM-framework (Kwakkel, 2017; Lempert et al., 2005) distinguishes between eXternalities (exogenous drivers), policy Levers (possible system interventions), system Relations (model equations) and Metrics (indicators for system performance), see Fig. 4. SETPs refer to climate-change induced socio-economic tipping points. Grey arrows indicate optional iterations over steps.

uncertain SLR, storm surges, house market behaviour and dynamic adaptive policy responses. Section 2 outlines the stepwise approach. Section 3 introduces the stylized case. Section 4 applies the stepwise approach to the case study. Section 5 discusses how the approach can be applied to other global cases. Section 6 concludes.

2. Stepwise approach

The stepwise approach to identification and decision support on SETPs is outlined in Fig. 2, which is described in more detail below and summarized here. Step 1–3 delineate and describe the socio-economic system and its possible SETPs. Step 4 identifies the conditions under which SETPs occur. Step 5–7 further assess the impacts of SETPs and formulate a policy advice for decision makers on adaptation and mitigation.

2.1. Step 1: System delineation

The first step delineates the system boundaries, involving a demarcation of the spatial and temporal borders, but also of the system aspects to be considered. These may include physical, ecologic, social, economic, institutional, political or ethical aspects. System delineation (as well as system description and tipping point definition) inevitably reflects a certain actor perspective; an understanding of how the world works (Karstens et al., 2007). Transparent description of this perspective is important because different actors might have different perspectives on how the system works and what are important system indicators.

Typically, the clearest SETP examples can be found on small scales in homogeneous systems, because of their uniform response to drivers of change (Scheffer et al., 2012) and limited possibilities for economic substitution (Van Ginkel et al., 2020).

2.2. Step 2: System description

The second step describes the system with the XLRM framework (applied on the case study in Fig. 4). This framework guides long-

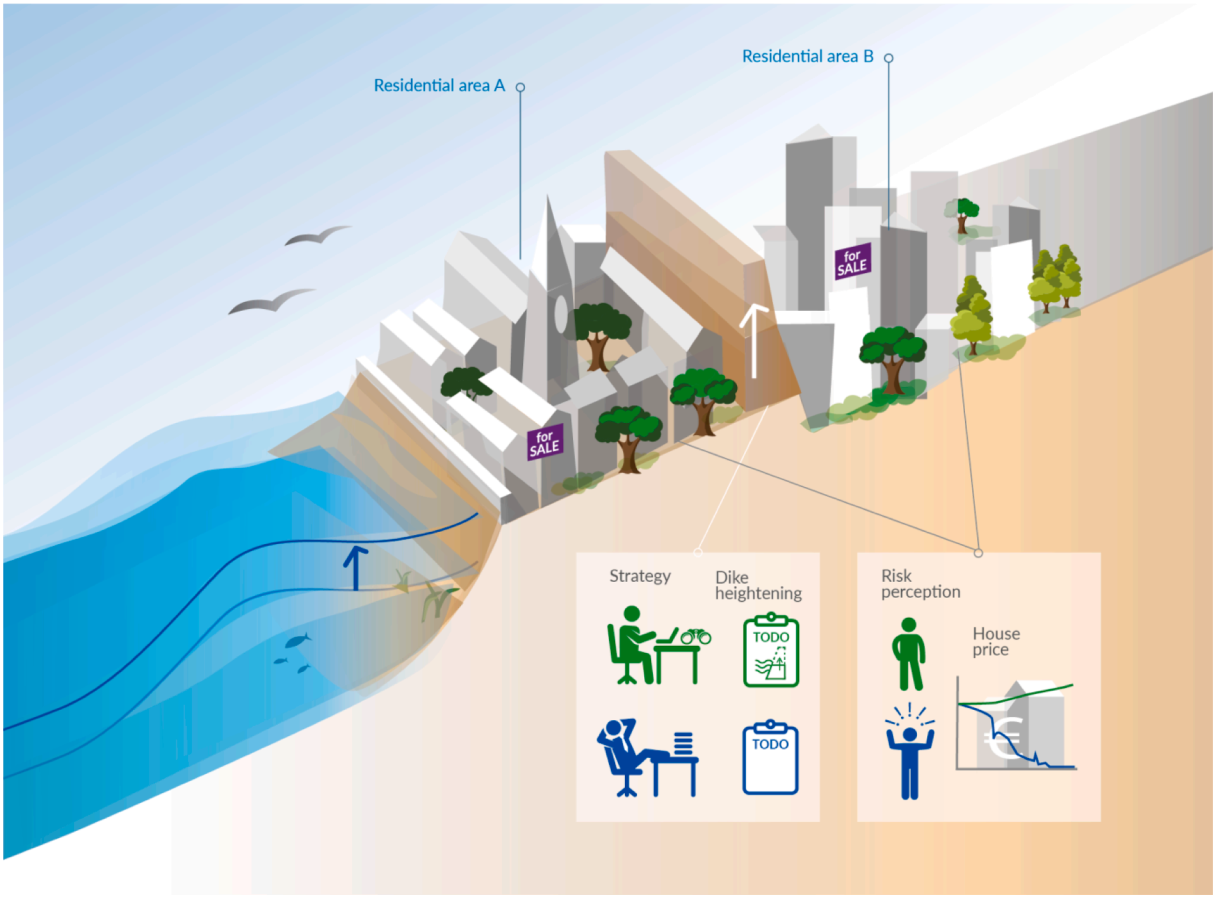

Fig. 3. Stylized presentation of the case study. Each year, the city experiences an extreme water level: the combined effect of sea level rise and a storm surge height. Residential area A is not protected, residential area B is protected by a dike which can be heightened due to adaptation. In both areas, the (perceived) flood risk is discounted in the house price.

term policy analysis by distinguishing (Lempert et al., 2005):

- Exogeneous uncertainties (X): the factors beyond control of decision makers on the system, such as climate change (RCPs) and external socio-economic development (SSPs);
- Policy levers (L): the adaptation policy actions or strategies for management of the system;
- Relations (R): the model linking exogeneous uncertainties and policy levers to outcomes of interest;
- and Metrics (M): indicators of system performance of interest to the decision maker, such as socio-economic or risk indicators.

Like the exogenous uncertainties (X), the policy levers (L) are external to the system, because they reflect the alternative strategies the decision maker can impose on the system from the outside. They may range from small incremental alternatives to the baseline strategy, to large transformative changes. Some measures may be so transformative, that their mere implementation could qualify as an SETP in terms of *transformative response* (Tàbara et al., 2021, also see box 1). However, such response SETPs are likely to be á priori assumed, and not á posteriori identified in step 4, unless they result from surprising model outcomes (e.g. resulting from complex behaviour in agent-based models), cf. Maier et al. 2020.

One complication in the study of tipping points in socio-economic economic systems (in contrast to their biophysical counterparts) is that human actors consciously and continuously adapt the system to change (Biggs et al., 2018; Van Ginkel et al., 2020). This raises the question whether adaptation should be understood as external or endogenous; as having a cause outside or within the system. The context for which the approach is developed, is the situation where a decision (or policy) maker is confronted with a potential SETP in a socio-economic system they are responsible for. The policy alternatives at the disposal of this decision maker may be modelled as completely independent of the system dynamics; in this case they are described as external policy levers (L). However, they can also be described as part of the system itself; in that case they are part of the model relations (R).

The model relations (R) can be described using statistical, system-dynamic, graph-theoretic, agent-based or computational (partial/general) equilibrium models (Filatova et al., 2016), or any hybrid combinations. Note that the non-linear tipping behaviour often results from reinforcing and stabilizing system feedback loops (Milkoreit et al., 2018).

2.3. Step 3: Tipping point operationalisation

The third step operationalises the SETP in terms of performance metrics (M) of the system, by showing how tipping point occurrence can be identified from system metrics, using the following SETP-characteristics (Milkoreit et al., 2018; Van Ginkel et al., 2020):

C1. rapid, abrupt change compared to typical rates of change in the system;
C2. indicating a transition from one relatively stable state before (B) to another relatively stable state after (A);
C3. with B being fundamentally different from A.

The operationalisation captures the non-linear, S-curve behaviour of the indicator metric timeseries. One method is to detect early

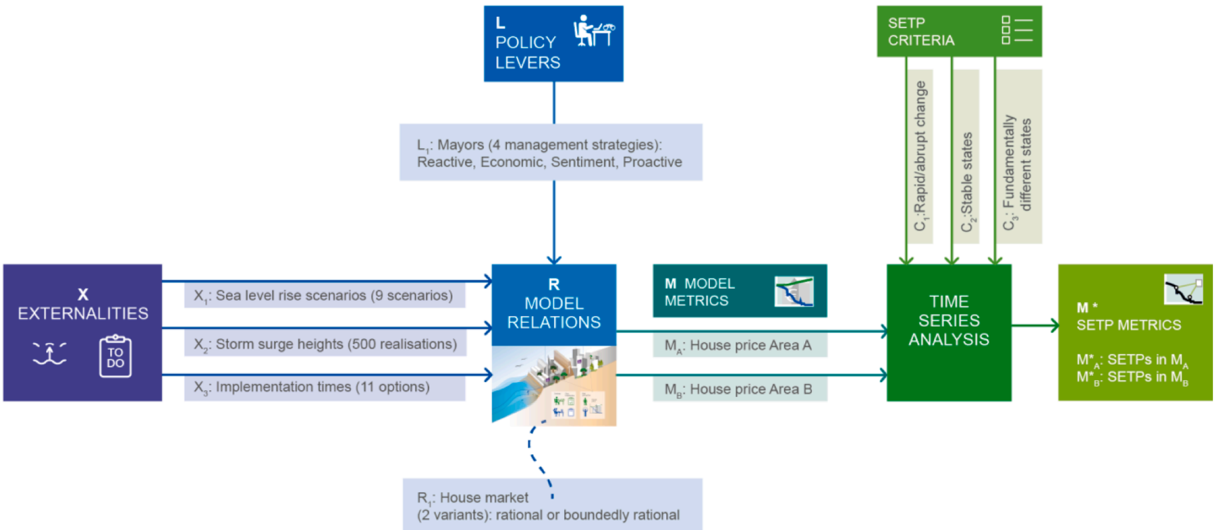

Fig. 4. Experimental set-up. Three exogenous uncertainties (X) and one policy lever (L) feed into the coupled physical-socioeconomic model (R), which has two alternative formulations for dynamics on the housing market. Each unique combination of X, L and R results in two timeseries with house prices for both residential areas (M). These timeseries are analysed to identify SETPs, described in the SETP-metric M*. See SI for model details.

warning signals of an approaching tipping point in the timeseries such as increasing autocorrelation, increasing variance, increasing skewness and flickering between two stable states (Scheffer et al., 2009; Singh et al., 2018). Another method is to detect the tipping point itself with a statistical test. For example, the null-hypothesis is a model with constant mean and variance for the entire metric time series, and the alternative hypothesis is a model with two states with different mean and variance which are separated by a step/change point (Carstensen and Weydmann, 2012). These change points can be detected with various algorithms (e.g. Andersen et al., 2009; Quandt, 1958, Truong et al., 2020). Yet another method is to tailor the three tipping point criteria (box 1) specifically to the metric time series, as done in our case study (Section 4.3).

2.4. Step 4: Tipping point identification

The fourth step identifies what model inputs cause tipping points in model outputs in the many possible futures, through an exploratory analysis (Moallemi et al., 2020). For example, scenario discovery techniques can identify for which combinations of input parameters (uncertainties X and policy levers L) the model behaviour of interest occurs (Hadjimichael et al., 2020; Kwakkel, 2017; Moallemi et al., 2020). Fig. 4 shows that to use these techniques, one intermediate step needs to be taken. The outcome timeseries (M (t)) of each experiment (an experiment is a model run with a unique combination of X, L and R) is tested on the occurrence of SETPs with the algorithm defined in the previous step. The results of this step are saved as a new metric M*.

2.5. Step 5: Impact assessment

The fifth step assesses the socio-economic system impacts of the identified tipping points. While step four only identified under which external circumstances (X and L) SETPs do occur, step five assesses how tipping has changed the socio-economic system. This starts within the initial system boundaries, by evaluating the state of model variables after the tipping point. For example, when the model relations (R) are described with an agent-based model, one can examine what the socio-economic conditions after the tipping point imply for the different actors represented in the model. Or, when using a system-dynamic model, one could evaluate the model variables after the tipping point, and reflect on what they tell about the new state of society and the economy.

Additionally, impacts beyond the initial system boundaries can be explored, by widening the spatial boundaries, reasoning beyond the time horizon, or beyond the aspects included in the initial analysis. For example, if the tipping point involves the collapse of a company or industry, the impact on the wider economic sector can be studied with a sectoral-economic or macro-economic model. If one suspects that the local SETP may also cause a tipping point on a larger scale, the feedback loop from step five to step one could be triggered (Fig. 2), repeating the analysis with widened system boundaries.

2.6. Step 6: Action identification

The sixth step identifies the possible actions that a decision maker can take to anticipate or avoid SETPs, or to mitigate the impacts of their occurrence. This starts by assessing the effectiveness of the policy levers that were included in the model. When possible new actions are identified, the feedback loop from step six to two can optionally be triggered, in which the actions are added as new policy levers, and their effectiveness is evaluated. An action can also be to monitor the variables that provide an early warning of system change.

2.7. Step 7: Decision support

In the last step, the lessons learned are translated to adaptation, mitigation and monitoring policies. Arguably, adaptation is most relevant for local decision makers since it directly limits local climate risk, while mitigation depends on actions that are typically taken by other jurisdictions. When in a qualitative approach concrete policy levers were included, one can reflect on their effectiveness to prioritize actions. We further recommend reflecting on the conditions that led to SETPs. This can inform policy to monitor certain key system indicators providing early warning of SETPs, and to timely intervene in the system.

3. Introduction to case study

Sea level rise is a global threat to low-lying coastal cities (Oppenheimer et al., 2020). Flood damage and exposed population are projected to strongly increase (Brown et al., 2018; Neumann et al., 2015; Vitousek et al., 2017), even with large adaptation investments to maintain constant flood probability (Hallegatte et al., 2013). It is relevant to explore the many possible futures of coastal cities on the occurrence of SETPs because SLR-projections are uncertain due to possible ice-sheet instability and increased mass-loss from Antarctica (Bamber et al., 2019; Horton et al., 2020; Le Bars et al., 2017). Moreover, coastal cities may experience non-linear impacts and possibly tipping points from increasing flood risk (de Koning et al., 2019; de Koning and Filatova, 2020; Haasnoot et al., 2020; Taherkhani et al., 2020; Barnard et al., 2021). Rotterdam is an interesting case for illustrating our stepwise approach in the context of this global challenge, because most of the city is exposed to coastal flooding while also having a high protection level. Moreover, storylines leading to possible SETPs for the city have been proposed in scientific literature (Haasnoot et al., 2020; Olsthoorn et al., 2008; van Ginkel et al., 2020), by the Dutch central bank (Caloia and Jansen, 2021), and in public debate (Bregman, 2020), but as of yet a systematic quantitative assessment of SETPs is lacking.

Rotterdam is the second largest city in The Netherlands and, located in the Rhine-Meuse Delta, it hosts the largest port of Europe.

Dikes and storm surge barriers protect the polders against coastal and riverine floods, protecting against a 1:10,000 year flood. Besides the low-altitude polders (-2 m), Rotterdam also has significant portions of unprotected areas which are elevated just above mean sea level (+3 to 5 m). Earlier studies found no technical or financial barriers for Rotterdam's flood protection for a SLR up to 105 cm SLR by 2100, although around 40–50 cm, the Maeslant storm surge barrier might no longer suffice, which requires new actions (Kwadijk et al., 2010). Under more extreme SLR scenarios, the current strategy might need more radical transformation, and the implementation times of the associated measures might become a limiting factor (Haasnoot et al., 2020). Explorations of a 5 m SLR scenario confirmed that constraints to coastal adaptive capacity were not technical, engineering or cost-benefit in nature, but rather social and political (Olsthoorn et al., 2008; cf. Hinkel et al., 2018). Experts suggest possible decreasing investments, hampered economic development and

Fig. 5. Illustrative runs to demonstrate model behaviour. Panel 1 shows two extreme water level scenarios: each scenario is the sum of a storm surge and sea level rise scenario. Each extreme water level scenario is combined with two management strategies, the panel also shows the timing and resulting dike heights from dike heightening measures. Panels 2AB show the flood damage and near miss history of the small unembanked area A (Panel 2A, 21st century) and the embanked city centre area B (Panel 2B, 22nd century). Panels 3AB show the flood risk perception of residents of both areas. Panels 4AB indicate the development of the house prices when assuming a rational versus a boundedly rational housing market.

falling house prices in the areas exposed to large flood risk, potentially resulting in SETPs (Olsthoorn et al., 2008; van Ginkel et al., 2020).

4. Application of steps to case study

To apply the stepwise approach to the case study, we developed a stylized coupled physical and socio-economic model for an archetypical city with characteristics of Rotterdam, from which lessons can be learned for other cities worldwide. It simulates long-term development of flood risk and house prices under various dynamic adaptive strategies and many possible futures, as described in the SI (Section SI 1), also see ‘Data and code availability’.

4.1. Step 1: System delineation

Spatially, the system is demarcated as two residential areas of Rotterdam (Fig. 3). Residential area A is elevated 3 m above mean sea level and is only protected by a small 0.5 m flood wall and is further considered as ‘unembanked’. Residential area B is 1 m below mean sea level and is embanked with a 4.5 m high dike that can be heightened (Figure SI 1). Temporally, the future of the region is explored from 2020 till 2200 to capture the long-term impact of adaptation decisions and the effect of a possible acceleration of SLR in the 21st century (Le Bars et al., 2017). The focus is on these system aspects: development of flood risk, flood risk perceptions, and their impact on the house price, aggregated per residential area. We restrict ourselves to public sector adaptation measures, which ignores household adaptation like insurance or floodproofing. In the Netherlands, it is currently not possible to buy insurance against coastal flooding. In the polder situation (Residential area B), storm surge water levels may easily reach 3–5 m above polder ground level (see Fig. 5, panel 1). Therefore, household floodproofing measures are (nowadays) rarely applied, making flood protection completely dependent on dikes. For simplicity, we kept the flood wall at Residential Area A constant, to create a reference case without adaptation.

4.2. Step 2: System description

The core of our storyline is that flood risk affects the house price, as is supported by empirical research (Beltrán et al., 2018; Bin and Landry, 2013; Bosker et al., 2019). The flood risk increases due to SLR but can be reduced by dike heightening measures taken by the government. Flood and near-miss events abruptly elevate the risk perception of residents, which declines over the course of time if nothing happens (Bin and Landry, 2013; McNamara and Keeler, 2013; Tonn and Guikema, 2018).

Structuring the system along XLRM (Fig. 4), there are three external uncertainties (X). The magnitude and rate of sea level rise (X_1) depends on (amongst others) the RCP scenario and the potential collapse of the icesheets, see Figure SI 3 (Bamber et al., 2019; Horton et al., 2020; Le Bars et al., 2017). The height of storm surge events (X_2) are stochastically drawn from an extreme value distribution (Sterl et al., 2009), on a yearly basis. The implementation times of flood protection measures (X_3) can also vary (Haasnoot et al., 2020). The system can be managed by one policy lever (L_1) which can be set to four archetypical public sector flood risk management strategies, reflecting a continuum from reactive to proactive hard protection strategies (Oppenheimer et al., 2019). The ‘reactive’ strategy acts upon near miss or flood events. The ‘economic’ strategy anticipates the objective flood risk; the ‘sentiment’ strategy the perceived flood risk. The ‘proactive’ strategy seeks to maintain dike protection levels on ambitious target levels (Table SI 4).

The model relations (R) are illustrated with example model runs in Fig. 5 and summarized in Figure SI 2. The storm surge heights are combined with the sea level rise scenario, giving an extreme water level per yearly timestep (Fig. 5, panel 1), Section SI 1.1. Protection against these extremes in area A is given by the elevation of the residential area, and in area B by a dike, which can be heightened by adaptation. In case of a flood, the damage to the unembanked area (panel 2A) or the embanked area (panel 2B) is calculated. These panels also show any near-miss events in which floods nearly occurred, Section SI 1.2. Flood and near-miss events heighten the risk perception per area (panel 3A and 3B); these perceptions decline in years when nothing happens (Aerts, 2020), Section SI 1.4. The model relations have one variable component (R_1): the behaviour of the housing market. The rational housing market discounts the *actual flood risk* in the house price, whereas the boundedly rational housing market discounts the *perceived flood risk* in the house price (Fig. 5, panel 4A and 4B), Section SI 1.5. The perceived flood risk may strongly deviate from the actual flood risk due to the experience of flood events and social interactions between the areas (Botzen et al., 2009; Haer et al., 2017; Tonn et al.,

Table 1
Formalisation of tipping points criteria, tailored to the Dutch house market, see SI for details.

Criterion	C1: Rapid, abrupt change	*C*2: Stable states	C3: Fundamentally different states
Model indicator threshold	The first-order derivative of the house price is above a threshold	The variance in the states before (B) and after (A) are above a threshold	The mean house prices in the state after and before are substantially different
Mathematical implementation	$M'_{RA}(t) = \frac{dM_{RA}(t)}{dt} \lvert M'_{RA}(t) \rvert \rangle c_1$	$\widehat{\sigma}_t^2(W_{t,B}) > c_2 \cap \widehat{\sigma}_t^2(W_{t,A}) > c_2$ With: $W_{t,B} = \{M_{t-d-n}, M_{t-d-n+1}, \cdots, M_{t-d}\}$ $W_{t,A} = \{M_{t+d}, M_{t+d+1}, \cdots, M_{t+d+n}\}$	$\frac{\lvert W_{t,B} - W_{t,A} \rvert}{W_{t,B}} > c_3$With: $\overline{W_t} = \frac{1}{n}\sum W_t$
Selected thresholds	$c_1 = 0.15M(t=0)_{RA}$	$c_2 = 10^9 \quad €^2$ $d = 3 \quad year$ $n = 4 \quad year$	$c_3 = 0.1$

2019). The objective flood risk only depends on the state of the flood protection, whereas the perceived flood risk combines the objective flood risk with the risk perception, Section SI 1.4.

The model is evaluated using two metrics (M): the development of the house price in the outer-dike area A (M_A) and the house price in the embanked city centre (M_B). Additional illustrative model runs highlight characteristic behaviour under different management strategies (Figure SI 7,8), storm surges scenarios (Figure SI 9) and implementation times (Figure SI 10).

4.3. Step 3: Tipping point operationalisation

We operationalise a SETP as a timestep t with rapid, abrupt change (C1) separating two substantially different (C3), stable states (C2), in the house price $M_{RA,t}$, of residential area RA. These three criteria are tailored to the Dutch housing market (Table 1, Figure SI 14). Compared to observed house price changes (Section SI 3.1), a yearly change of more than 15 % is considered rapid, abrupt change (C1). A persistent change of more than 10 % is considered substantially different (C3), calculated over a 4-year rolling time window W. The variance, calculated over the same time window, is compared to a model-specific threshold that was identified iteratively. The tipping point detection algorithm is described in Section SI 3.1.

Fig. 6 shows that not all large house price fluctuations correspond to tipping points. Panel A shows a gradual declining house price, without rapid change in any of the years (C1 not met). Panel B shows a point of rapid change, with a stable state before, but not after the tipping point ($C2$ not met). Panel C shows two points of rapid change with stable states before and after, however, in both cases these states are not substantially different (C3 not met). Panel D shows three perfect examples of SETPs (C1-C3 met).

In the decision context of a coastal city, an abrupt shift to a period of large house price instability (Fig. 6B) might be just as policy relevant as price collapse to a stable state (Fig. 6D). Therefore, in the tipping point identification phase, we also include these rapid transitions from stable to unstable states (Fig. 6B).

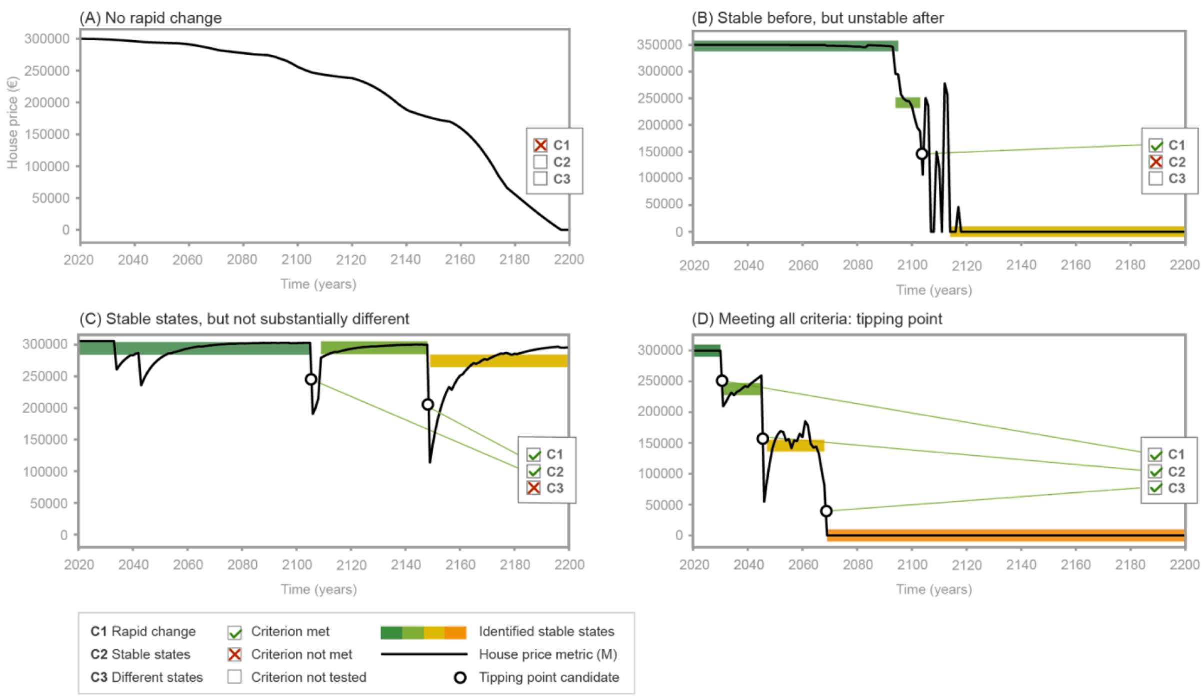

Fig. 6. Four examples of how the SETP-identification algorithm tests if points in the metric house price time series M(t) meet the tipping point criteria (C1-C3). Panel A results from a gradual risk increase in a rational housing market under low sea level rise. This happens in unembanked area A where no adaptation takes place, and eventually so much damage is expected that houses are worth nothing. Panel B results from slow and reactive adaptation to fast sea level rise, in combination with a boundedly rational housing market. When a flood disaster strikes, a strongly elevated risk perception causes a house price crash in Area B. The disaster triggers adaptation, but this is not fast enough to keep up with sea level rise. The house price temporarily restores upon completion of new measures, and drops again when new floods or near misses hit the city. Panel C results from a boundedly rational housing market under very low sea level rise in the unembanked area A. As displayed by the increasingly deep downward spikes, there is a gradual increase in risk, that only has a temporarily effect on prices after a near miss event or flood. House prices recover because risk perception declines over time. Panel D results from no adaptation to a high sea level rise in area A, in combination with a boundedly rational housing market. Floods or near miss events cause abrupt house price drops to significantly lower levels. House prices do only slowly recover because the risk keeps increasing while trust restores. When new events strike, house prices drop to even lower levels. See Section SI 3 for more details.

4.4. Step 4: Tipping point identification

Each of the 396,000 experiments selects a unique combination of a sea level rise scenario X_1, a storm surge series X_2, a measure implementation time X_3, flood protection strategy L_1 and a housing market model R_1 (Fig. 4). Each experiment delivers two time series, the house price in area A $M_A(t)$ and area B $M_B(t)$, in which tipping points are identified (Section 4.3). The EMA-workbench (Kwakkel, 2017) was used to systematically detect combinations of input-parameters resulting in time series with tipping points, and to create a dimensional stack visualization (Suzuki et al., 2015) (Fig. 7). Additionally, the SI presents the results of two alternative techniques for exploratory analysis: feature scoring (Section SI 4.1) and scenario discovery (Section SI 4.2).

In the most extreme SLR scenarios (SLR scenario 1 and 2, Fig. 7), SETPs in the embanked City Centre occur under all four management strategies. Combined with a reactive strategy, SETPs occur even with very short measure implementation times (4 years for a small measure). The rate of SLR in these scenarios is too high to adequately anticipate with a reactive flood risk strategy. With the most proactive strategy, however, SETPs can be avoided if measures can be quickly implemented, i.e. within 7 years or faster. The proactive strategy best resembles the current flood protection strategy in Rotterdam. Observed implementation times of small dike heightening measures are typically shorter than 10 years, whereas the construction of large storm surge barriers may take 20–40 years (Haasnoot et al., 2020).

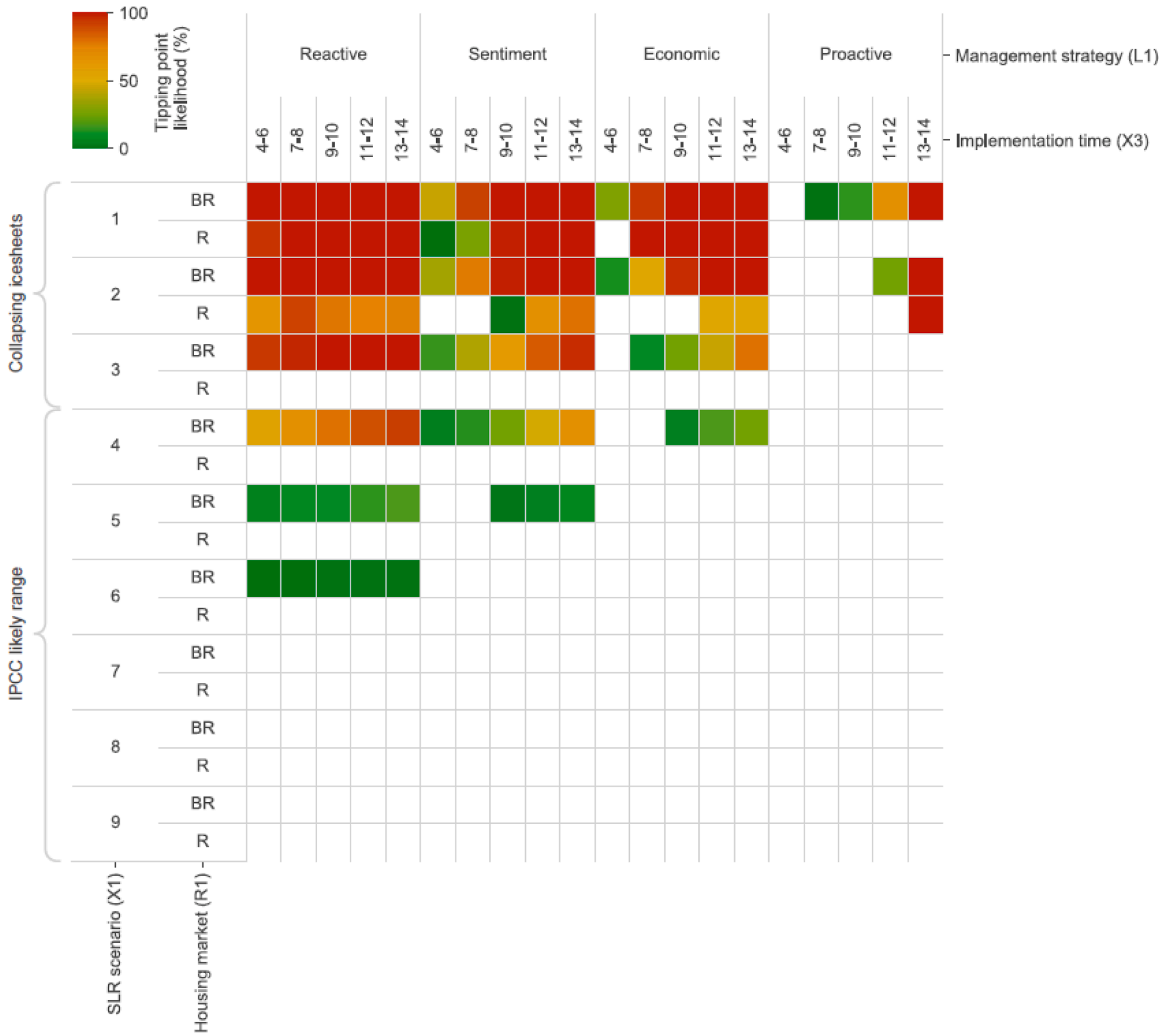

Fig. 7. Dimensional stack visualization of combinations of input parameters leading to tipping points in the housing price in the City Centre. The y-axis captures the uncertainty in SLR scenario (X_1) and the housing market (R_1) which may be rational (R) or boundedly rational (BR). The x-axis captures the uncertainty in the adaptation strategy (L_1) and the measure implementation time (X_3). Each grid-cell indicates the percentage of storm surge scenarios (X_2) causing tipping points in the house-price before 2200. Coloured grid cells indicate a percentage greater than 0, white grid cells indicate no tipping points.

In the more moderate SLR scenarios 3–6 (note that 4–9 roughly correspond to the IPCC SROCC 'likely range', Figure SI 3) SETPs may still occur in the City Centre, but the pattern is more varied. In the proactive strategy, no SETPs occur. In the other three strategies, SETPs only occur in the boundedly rational housing market where flood risk perceptions (rather than rational risk) determine house prices. In other words: in an economic rational market, no busts of house prices are expected under moderate SLR scenarios. In these markets, the risk only gradually increases and is reduced by adaptation before becoming substantial. However, if housing prices depend on more strongly fluctuating risk perceptions, such as in the boundedly rational market, rapid drops in house prices occur. The difference between these two housing markets can be seen in Fig. 5, panel 4B.

In the low-end SLR scenarios (7–9), no tipping points occur in the City Centre. But in the unembanked area A, they do occur, even before the year 2100 (Figure SI 17).

4.5. Step 5: Impact assessment

What could be the impact of a house price collapse in the small unembanked area A? If market forces dominate, the residents who can afford it will sell their properties and relocate to safer grounds whereas low-income and less risk-adverse residents might be attracted by the lower prices. This could trap low-income households in the area until the point is reached where the area becomes unliveable (de Koning and Filatova, 2020). More likely, the government will intervene, by forcing retreat or entire redevelopment of the area.

A house price collapse in the (much larger) city centre (area B) would most likely hamper real estate investments and reduce regional economic growth (Beltratti and Morana, 2010). It could also increase demand and inflate prices of property on safer grounds. To the extent that the collapse was driven by unrealistically high risk perceptions, market forces and trust may restore prices to rational levels.

These urban-scale impacts are likely to spill over to the national scale. Especially in the Dutch situation, where the flood-prone Randstad megapolis hosts about half of the population and GDP (CBS Statistics Netherlands, 2021b), any serious concern about flood safety will trigger large debate. Large parts of the Netherlands currently are less protected than Rotterdam because of smaller economic activity (Kind, 2014). This observation exemplifies how assessment of the wider system context in step 5 could trigger the feedback loop to step 1: when reflecting on the impact of an SETP for Rotterdam, one discovers that this cannot be seen in isolation from the spatial planning strategy of the entire country and one may repeat the analysis with wider system boundaries.

4.6. Step 6: Action identification

The experimental design included the widely observed *protect* strategy of incremental dike heightening measures to protect the city centre. The proactiveness by which this strategy was carried out was implemented as an external policy lever, so that the timing of individual measure implementation could be endogenously simulated. The results show that the *protect* strategy is mainly effective in moderate SLR scenarios and when it is carried out proactively, otherwise SETPs might occur. Monitoring of SLR, flood events and changes in house prices could provide early warning of an approaching SETP. Besides this incremental *protect* strategy, one could also *accommodate* to make the city less vulnerable to floods, *advance* by expanding and elevating the city seaward, or *retreat* by relocating houses to safer grounds (Mach et al., 2019; Oppenheimer et al., 2019).

In the unembanked residential area, one could for example *accommodate* by implementing loss-reduction measures, which reduce damage by 70 % for inundations < 1 m; the study of Haer et al. (2017) shows that this is an effective means to cope with moderate SLR scenarios. More drastic *accommodation* would be to elevate entire residential areas. The *advance* response is already used in the newly reclaimed areas of the Port of Rotterdam, which are constructed 5 m above current mean sea level (Boer et al., 2009). By using the feedback loop from step six to step two, one could add the flood proofing and elevation actions as a new policy levers and explore its impact on SETP-occurrence.

On the national scale, a *retreat* strategy could be the relocation of city residents to higher grounds in the east of the Netherlands. Especially for areas with small socio-economic importance, managed retreat could be more than a mere left-over strategy, provided it is embedded in sound national spatial planning (Mach et al., 2019; Siders et al., 2019). On the international scale, a very drastic *advance* action would be the construction of the Northern European Enclosure Dam (Groeskamp and Kjellsson, 2020) enabling water level control or even complete reclamation of the North Sea. Such transformative measures can be considered socio-economic policy tipping points (Herrfahrdt-Pähle et al., 2020; van Ginkel et al., 2020), in terms of *transformational response* SETPs (box 1), which could be added as a policy lever to the current model set-up in step 2. Evidently, it would be more meaningful to do such analysis with wider system boundaries, one could then also decide to include the decision-making process on local retreat as endogenous system behaviour, and study it as an impact SETP.

4.7. Step 7: Decision support

What policy advice can be given based on the SETP-analysis? First, a very proactive flood risk management strategy can already avoid most of the SETPs. Second, the implementation times of flood protection measures need to be sufficiently short to keep pace with the rate of sea level rise. Under high-end sea level rise, even a very proactive management strategy might fail if the measure implementation time is too long. This is alarming because at present, technical challenges and complex coastal management frameworks often cause long implementation times. Third, management of flood risk perception is very important: having adequate flood protection is one thing, convincing the public that it is adequate is another. When all buyers and sellers on the house market are aware of gradual changes in flood risk, large fluctuations in risk perceptions and related house price booms and busts may be avoided. Whereas the other insights also emerge from other studies as good management practices, this finding most uniquely follows from the SETP-perspective taken in study. It highlights that for avoiding SETPs, socio-economic processes like opinion dynamics and risk perceptions could be as important as technical adaptation measures (cf. Smith et al., 2022). Fourth, monitoring of sea level rise and ice sheet dynamics is crucial to detect any possible acceleration of SLR early. In the most extreme scenarios, there is a risk that the *protect* strategy proves to be a lock-in strategy which ultimately fails. Then a possible switch to a different coastal adaptation strategy such as *advance, accommodate,* or *retreat* should be anticipated as soon as possible, because such fundamental policy shifts may require much longer implementation times (Termeer et al., 2017).

5. Discussion

The aim of this study was to present a stepwise approach that identifies under what conditions SETPs may occur and guides policy aimed at preventing adverse SETPs or supporting positive SETPs. With the help of a stylized model we explored many possible futures of a coastal city and did identify SETPs. Sudden house price collapses occur when extreme sea level rise is compounded by: reactive flood risk management, risk perceptions dominating house price dynamics, or long implementation times of flood protection measures. A frequent cause is when during several decades the actual flood risk gradually increases to substantial levels without triggering action, because by chance there are no major storm surges. When a trigger event eventually occurs, this causes a large drop in house price, because the substantial flood risk is suddenly and amplified (due to risk overestimation) discounted for in the house price. This eventually triggers large flood protection measures, which take time to implement. In the most extreme SLR scenario's, the rate of sea level rise exceeds the speed and magnitude at which the government can respond, and the house prices remain unstable.

These findings indeed help to inform policy aiming at preventing SETPs; Section 4.7 presented four policy recommendations for coastal cities like Rotterdam. Either a reactive 'wait-and-see' policy, a failure to manage flood risk perceptions, or a delayed implementation of a crucial flood protection measure may cause an SETP in high-end SLR scenarios. If this can happen to a relatively prosperous city with very high current protection levels like Rotterdam, we may expect that in other coastal cities, SETPs may happen earlier and also in less extreme SLR scenarios because of weaker institutional settings and less resources for adequate response (cf. Hinkel et al., 2018; van Ginkel et al., 2018). This confirms findings of other studies that stress the need for a proactive, adaptive flood risk management strategy which monitors important signpost and responds timely (e.g. Haasnoot et al., 2018).

Given the stylized relations in the model, the case study results should be interpreted with caution. The SLR-scenarios 1 and 2 follow the $\geq$ 95 % tail of the probability distribution (Figure SI 3), meaning that even when accounting for ice sheet instabilities, these have low likelihood (Bamber et al., 2019). Since the house markets are archetypes of actual dynamics, the price fluctuations under extreme conditions are rather large. Real-world house price fluctuations can also be large: in 1999, the house price in Amsterdam increased by 19 % (CBS Statistics Netherlands, 2021a) and from 2006 to 2009, nationwide property prices in the US dropped by 38 % (Nneji et al., 2013). The policy responses are generalized features of possible dynamic adaptive strategies, whereas reality is more nuanced.

However, our objective was to illustrate the stepwise approach, for which our model is suitable due to three characteristics. First, the short runtime allows for the exploration of many possible futures, uncertainties and policies. Second, the model relations cause non-linear behaviour under some conditions giving it the potential to exhibit tipping points. Third, the model dynamically adapts over time, which is an indispensable feature to represent a highly adaptive socio-economic system on longer timescales. For other applications of the stepwise approach, models with these three characteristics are suitable, such as some agent-based, system-dynamic or graph-theoretic models (Filatova et al., 2016).

How can the model approach be applied to other coastal zones? The current model structure contains many generic aspects applicable to other areas, such as the built-in sea level rise scenarios, a storm surge generator, a flood damage and risk calculator, dynamic adaptive dike heightening strategies, as well as a risk perception, house price, and SETP-identification module. These can easily be adjusted to the local context. At the same time, some model relations will need to be updated to represent the myriad of complex dynamic adaptive processes that dominate in different socio-economic, institutional and biophysical contexts around the globe. For example, coastal adaptation in the USA relies heavily on adaptation by households, firms and communities, and not solely on government interventions. Also, the role of insurance is highly relevant (Ruig et al., 2022). To mimic house-price and adaptive dynamics, the model needs to be downscaled to individual household actors, which could build on studies like De Ruig et al. (2022) for New York City. In a city like Miami, there can be technological limits - a highly permeable underground - that constrain the dike heightening solution and need to be accounted for. A city like Beira (Mozambique) suffers from large financial barriers due to a very poor credit rating, which means that a strategy cannot be based on cost-benefit analysis alone, but also relies heavily on the availability of financial means. Another aspect is poor maintenance of coastal flood protection infrastructure in times of economic or institutional downturn, which could be represented with enhanced failure probabilities of the flood protection infrastructure. Furthermore, the range of management strategies can be extended to *retreat, accommodate*, and *advance*, to complement the current *protect* strategy, as discussed in section 4.5 and 4.6.

In future research, the stepwise approach helps to get a grip on the core elements, assumptions, definitions and methodologies of research on policy relevant tipping points. The advantage of using the steps is that they force reflection on important SETP-characteristics. First, SETPs typically occur on specific spatial, temporal and sectoral scales and are less distinct on other scales. The analysis therefore initially focusses on a strictly delineated scale, whereas possible spill-overs to other scales are later examined in the impact analysis step. A related characteristic is that SETPs may unevenly impact different stakeholder groups, because socio-economic reconfiguration typically has winners and losers. Transparency about the reflected perspective may avoid controversy about tipping point terminology and examples. A second advantage is that one does not have to decide between these possible conflicting views on how the system works, because multiple possible system relations (such as our two types of house markets) can be represented. Third, SETPs seem rare phenomena resulting from specific compound biophysical and socio-economic events, located somewhere in the large uncertainty space. The approach transparently describes relevant uncertainties and provides a systematic procedure to identify the (rare) points of interest. Fourth, the approach delivers a concrete policy advice by identification of adaptation and mitigation actions, and recommendation of key monitoring variables.

Although our focus has been quantitative, the stepwise approach can also be used for qualitative assessments. In step 3, a narrative would operationalise the SETP by describing two more or less stable, fundamentally different states at both sides of a critical threshold, and how a rapid shift between these states may occur. Such descriptions may be supported from archaeological evidence (e.g. Tainter, 1988), scientific descriptions of socio-economic dynamics (e.g. McLeman, 2017) or from expert and stakeholder consultation (e.g. Olsthoorn et al., 2008). In step 4, a set of plausible qualitive future storylines would be developed, based on literature review or stakeholder interviews/workshops (e.g. Jack et al., 2020; Lopez et al., 2019; Wilby and Dessai, 2010; van Ginkel et al., 2020), that indicate under what conditions tipping points occur in the range of possible futures (cf. Otto et al., 2019). One pitfall of a qualitative approach is that anecdotical evidence or unrealistic views of particular stakeholders start dominating the storylines; in an earlier qualitative exploration of tipping points in the Dutch Delta, stakeholders had diverging and conflicting views on what could possibly happen (van Ginkel et al., 2020). A complementary model-based approach can help to assess the plausibility of storylines and to systematically explore large outcome spaces, which are hard to comprehend without computational support.

In-between qualitative and quantitative, one can also take a ‘metric-over-critical-threshold’ approach. Here, the metric itself does not show non-linear behaviour, but is known to have a critical threshold value, at which a transition between two stable system states occurs (Barnard et al., 2021). An example threshold is the 100-day rule used for analysing climate change impacts to ski resorts (Damm et al., 2014), indicating the minimum number of favourable snow days per year for a ski resort to be profitable. If snow conditions repetitively drop below this threshold, the ski resort will financially collapse (Vaghefi et al., 2021). The upside of the metric-over-threshold approach is that the complex non-linear behaviour around the tipping point does not have to be modelled. The downside is the a priori assumption that the threshold indicates an SETP; this assumption may be false in parts of the uncertainty space.

The fully quantitative approach also has specific challenges. The first is developing an algorithm that soundly detects SETPs. This challenge is more than just technical, because it highlights a tension between a strict system-dynamic understanding vs a more policy relevant understanding of tipping points (see Van Ginkel et al., 2022 for an example in transport networks). For our case, the situation where the house price abruptly dropped after a stable period and kept fluctuating without reaching a new equilibrium, does not meet all three SETP criteria, but is nevertheless policy relevant. We conclude that typically, the set of policy relevant points is larger than the set of perfect SETP examples, because large metric fluctuations are often policy relevant, even if they are not abrupt or persistent. Second, one needs to verify if initial model relations and boundary conditions are still valid when the system has tipped. By definition, the state after the SETP fundamentally differs from the state before. Therefore, other socio-economic mechanisms than initially modelled may dominate the model when the tipping point has passed. For example, in our case study the house price sometimes dropped to very low levels after the tipping point. At such below-market-value prices, the residential areas might also become available for redevelopment into industrial or port areas, or nature development. These price-stabilizing mechanisms are not incorporated in the model, but even if they would be included, the new equilibrium state would be fundamentally different, meaning the SETP definition is met. The value of the approach lies therefore mainly in detecting SETPs rather than precise forecasting how the new state will look like.

6. Conclusion

Climate change may cause socio-economic tipping points, which are uncertain but policy relevant. This study presents a stepwise approach that identifies under what conditions SETPs may occur and guides policy aimed at preventing adverse SETPs or supporting positive SETPs. This fills a niche in existing literature which mainly focussed on biophysical non-linearities and lacked a policy-relevant approach that accounts for many uncertainties. It adds to DMDU-literature an approach that explicitly accounts for tipping points.

The stepwise approach can range from qualitative, with stakeholder narratives, to quantitative, with models and exploratory modelling tools. Qualitative assessment is a resource efficient method to explore many mechanisms and quantitative assessment is important to verify these mechanisms. In a quantitative assessment, existing DMDU techniques such as scenario discovery are extended with a tipping point identification algorithm to investigate output timeseries. We found that the set of policy relevant points is typically larger than only the tipping points according to a strict system-dynamic understanding.

The case study suggests that even in a city that currently has very high protection levels (such as Rotterdam), house price collapses may occur if in a high-end sea level rise scenario, the government fails to act fast and proactively. Collapses result from sudden increases of public flood risk perceptions; managing these perceptions is therefore one of our policy recommendations. In the Dutch context, structural solutions to the most extreme SLR scenarios are found on larger spatial levels than the urban scale of this study. When monitoring reveals that a high-end SLR scenario is approaching, an intentional *transformative response SETP* towards an *accommodate* or *retreat* strategy could be triggered.

A natural progression of this study are new applications of the model to the long-term adaptive dynamics of other coastal areas around the world. It can investigate tipping points under different biophysical, socio-economic and institutional settings. The model code is open source and can be easily extended and tailored to the local context (see Data and code availability).

Future research can benefit from applying the stepwise approach; see Van Ginkel et al. (2022) for a recent application to transport networks. The system delineation, system description and tipping point operationalisation step provide insight into the assumptions underlying the assessment, which clarifies the applicability, validity and scope of the results. The exploratory modelling step systematically explores the relevant uncertainties which is imperative because SETPs are typically rare, compound events. The impact assessment revisits the choice of system scale, which can be decisive for finding tipping points or not. The steps eventually lead to a concrete policy advice, which moves a study beyond a mere analysis of SETPs as an interesting system-dynamic phenomenon, towards a concept that provides perspective of action for policy makers.

Application of the stepwise approach to cases where environmental change occurs in combination with non-linear socio-economic dynamics will contribute to a better understanding of socio-economic tipping points and will support policies to mitigate or adapt to them.

Data and code availability

All model code and data, also for reproduction of Figs. 5-7, can be found on GitHub through this https://doi.org/10.5281/zenodo.6782856.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All code and data can be found in the Supplementary Infomation and on the Github repository.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.crm.2022.100445.

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